Real-Time On-Chip Machine Learning Based Wearable Behind-The-Ear Electroencephalogram Device for Emotion Recognition

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Abstract: We propose a compact, low-power, behind-the-ear (BTE) wearable electroencephalogram (EEG) device with an on-chip machine learning (ML) pipeline for real-time emotion recognition. The device integrates multichannel dry electrodes, low-noise analog front end (AFE), microcontroller with on-chip neural accelerator, and optimized signal processing and classification models to perform affective state estimation at the edge. This paper describes the hardware architecture, embedded signal preprocessing, feature extraction, lightweight deep learning model design, model compression and quantization methods, and an evaluation strategy using publicly available and in-house datasets. We report design trade-offs for power, latency, and accuracy, and present a roadmap for clinical and consumer applications. Results from an implementation prototype (hardware emulation and software-in-the-loop) demonstrate promising classification accuracy with sub-200 ms end-to-end latency and sustained operation on a small battery for multiple hours. We conclude that on-chip ML in BTE-EEG wearables is a viable pathway toward private, low-latency emotion-aware applications.

Keywords: Behind-the-Ear EEG, wearable EEG, on-chip machine learning, emotion recognition, edge AI, low-power design, signal processing

INTRODUCTION

In this study, we propose an end-to-end emotion recognition system using an ear electroencephalogram (EEG)-based on-chip device that is enabled using the machine-learning model. The system has an integrated device that gathers EEG signals from electrodes positioned behind the ear; it is more practical than the conventional scalp-EEG method. The relative power spectral density (PSD), which is the feature used in this study, is derived using the fast Fourier transform over five frequency bands. Directly on the embedded device, data preprocessing and feature extraction were carried out. Three standard machine learning models, namely, support vector machine (SVM), multilayer perceptron (MLP), and one-dimensional convolution neural network (1D-CNN), were trained on these rich emotion classification features. The traditional approach, which integrates a model into the application software on a personal computer (PC), is cumbersome and lacks mobility, which makes it challenging to use in real-life applications. Besides, the PC-based system is not sufficiently real-time because of the connection latency from the EEG data acquisition device. To overcome these limitations, we propose a wearable device capable of performing on-chip machine learning and signal processing on the EEG data immediately after the acquisition task for the real-time result. In order to perform on-chip machine learning for the real-time prediction of emotions, 1D-CNN was chosen as a pre-trained model using the relative PSD characteristics as input based on the evaluation of the set results. Additionally, we developed a smartphone application that alerted the user whenever a negative emotional state was identified and displayed the information in real life. Our test results demonstrated the feasibility and practicability of our embedded system for real-time emotion recognition.

Emotion plays an important role in daily human life because they directly affect our ability to make decisions [1], [2]. Much attention has been paid to investigating and exploring the different methods of interaction and communication. between humans and machines. Of particular interest has been the area of enabling intelligent machines to understand human emotions. Over the centuries, most methods for recognizing human emotions have been based on facial expressions, speech, and gestures [3]. Although these techniques have produced good results, they are still constrained by a number of practical issues and are subject to human control. Methods using bio-signals have recently emerged as an area of immense interest in emotion recognition [4]. The commonly used bio-signals include body temperature, heart rate, electrocardiogram, and electroencephalogram (EEG) [5]. EEG signals have demonstrated their potential in emotion recognition [6]. EEG is an electrophysiological monitoring approach to record the cerebral electrical activity on the skin, typically by placing electrodes on the scalp [7]. Ear EEG is a technique that uses electrodes positioned in and around the ear to monitor brain activity [8]. Its superiority over the traditional EEG measurements that use electrodes placed on the scalp is its greater invisibility and wearer mobility; however, ear EEG has low signal amplitude [8]. Ear-EEGs are divided into two main groups based on the two measurement locations: (i) in-the-ear EEG that measures the signals from the areas within the concha and the ear canal [9] and (ii) behind-the-ear EEG that measures signals from different positions behind the ear lobe [10]. Currently, almost all emotion detection systems using EEG signals are computer-based and consist of two main parts: (i) an EEG-acquiring device having wearable wireless capability (Bluetooth) for data transmission and (ii) a computer for performing the emotion classification task [11]. This system is cumbersome and inconvenient because of the latency of the wireless technology; the system is also not real-time enough for the applications that require immediate results. Power spectral density (PSD) for EEG-based emotion recognition is an important feature that has proved effective in numerous studies [12], [13]. In this study, the PSD approach is used to decompose each EEG signal into five distinct frequency ranges, namely, delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50Hz). Then, the percentage of PSD that each EEG band occupies is calculated for feature extraction. By combining the functionality of an on-chip data processing system into a single TABLE 1. Summary of the technical parameters of the proposed device. device, the system may be utilized for real-time applications. Furthermore, using the behind-the-ear EEG instead of the scalp-EEG also makes the device more compact and comfortable for the daily user [14]. Machine learning has been increasingly integrated with EEG in various domains, including emotional detection, neural feedback training, epilepsy, rehabilitation, mental workload, and other fields [15]. In the realm of emotional detection, machine learning algorithms can be employed to analyze EEG signals for the identification and classification of diverse emotional states such as happiness, sadness, anger, and anxiety [16]. In stroke management, real-time health monitoring systems like HealthSOS [17] have incorporated machine learning techniques to predict the prognosis of stroke. Moreover, machine learning has been implemented in advanced driver-assistance systems to identify neurological biomarkers induced by driving [18]. In sleep studies, machine learning has been utilized to assess EEG-biomarkers to predict different sleep stages [19]. Tiny ML is a growing area of interest for implementing machine learning to embedded systems and investigating various models that can operate on low-powered devices such as mobile phones or microcontrollers [20]. Therefore, in this study, we developed an embedded device that deploys a tiny machine learning (Tiny ML) model using EEG signals measured by electrodes placed behind the ear for emotion detection applications. We investigated the performance of three common models for emotion classification: the support vector machine (SVM), multilayer perceptron (MLP), and one-dimensional convolutional neural network (1D-CNN). The model with the highest level of performance accuracy was chosen for use in our proposed embedded device.

LITERATURE SURVEY

The main contributions of this research can be summarized as follows: Firstly, a thorough hardware and firmware design of our wearable customed-designed behind the ear EEG device was developed for direct on-chip data. collection and processing. Secondly, the performance of a proposed 1D-CNN model with hyper parameter tuning was evaluated and compared with two other proposed models, MLP and SVM, for emotion recognition using ear-EEG signals collected from the device, on both subject-dependent and subject-independent cases. Finally, the practical application of a real-time behind-the-ear EEG-based emotion recognition system was demonstrated. The entire process of data collection, preprocessing, and deploying and running the model was performed directly on the real-time on-chip device.

The ear EEG method is a novel approach to brain signal acquisition that overcomes the constraints of traditional EEG-based BCI systems. The EEG signals in this study are obtained using passive electrodes similar to those used for scalp-EEGs, except they are positioned around the ears. As a result, ear EEG setup is significantly simpler and less timeconsuming than scalp EEG. used three electrodes placed behind the right ear, where the potential amplitude for the visual stimuli was excellent. EEG signals were acquired from three distinct locations located in the mastoid region positioned posterior to the right ear.

We present a framework for Emotion Recognition based on supervised learning techniques. The performance metric utilized in this context is the handover failure rate. The framework assesses mobility issues, encompassing both too-early and too-late handovers, to identify instances of Emotions in humans.

It allows for quick training and prediction, making it suitable for scenarios where computational efficiency is crucial. It can provide rapid insights into the likelihood of emotions in human based on their health data. However, it may not capture intricate relationships between features as effectively as more complex algorithms

A. Haag,The detection of emotion is becoming an increasingly important field for human-computer interaction as the advantages emotion recognition offer become more apparent and realisable. Emotion recognition can be achieved by a number of methods, one of which is through the use of bio-sensors. Bio-sensors possess a number of advantages against other emotion recognition methods as they can be made both inobtrusive and robust against a number of environmental conditions which other forms of emotion recognition have difficulty to overcome. In this paper, we describe a procedure to train computers to recognize emotions using multiple signals from many different bio-sensors. In particular, we describe the procedure we adopted to elicit emotions and to train our system to recognize them. We also present a set of preliminary results which indicate that our neural net classifier is able to obtain accuracy rates of 96.6% and 89.9% for recognition of emotion arousal and valence respectively.

I. Hussain, S. Young, and S.-J. Park,Physiological signals are immediate and sensitive to neurological changes resulting from the mental workload induced by various driving environments and are considered a quantifying tool for understanding the association between neurological outcomes and driving cognitive workloads. Neurological assessment, outside of a highly-equipped clinical setting, requires an ambulatory electroencephalography (EEG) headset. This study aimed to quantify neurological biomarkers during a resting state and two different scenarios of driving states in a virtual driving environment. We investigated the neurological responses of seventeen healthy male drivers. EEG data were measured in an initial resting state, city-roadways driving state, and expressway driving state using a portable EEG headset in a driving simulator. During the experiment, the participants drove while experiencing cognitive workloads due to various driving environments, such as road traffic conditions, lane changes of surrounding vehicles, the speed limit, etc. The power of the beta and gamma bands decreased, and the power of the delta waves, theta, and frontal theta asymmetry increased in the driving state relative to the resting state. Delta-alpha ratio (DAR) and delta-theta ratio (DTR) showed a strong correlation with a resting state, city-roadways driving state, and expressway driving state. Binary machine-learning (ML) classification models showed a near-perfect accuracy between the resting state and driving state. Moderate classification performances were observed between the resting state, city-roadways state, and expressway state in multi-class classification. An EEG-based neurological state prediction approach may be utilized in an advanced driver-assistance system (ADAS).

W. Chen, S. Ouyang, W. Tong, X. Li, X. Zheng,The rapid growth in miniaturization of low-power embedded devices and advancement in the optimization of machine learning (ML) algorithms have opened up a new prospect of the Internet of Things (IoT), tiny machine learning (TinyML), which calls for implementing the ML algorithm within the IoT device. TinyML framework in IoT is aimed to provide low latency, effective bandwidth utilization, strengthen data safety, enhance privacy, and reduce cost. Its ability to empower the IoT device to reliably function without consistent access to the cloud services while delivering accurate ML services makes it a promising option for IoT applications seeking cost-effective solutions. Especially in settings where inadequate connectivity is common, TinyML aims to provide on-premise analytics which will add substantial benefit to IoT services. In this article, we introduce the definition of TinyML and provide background information on diverse related technologies stating their strengths and weaknesses. We then show how TinyML-as-a-service is implemented through efficient hardware-software co-design. This article also introduces the role of 5G in TinyML-IoT scenario. Furthermore, it touches on the recent progress in TinyML research in both academia and industry along with future challenges and opportunities. We believe that this review will serve as an information cornerstone for the IoT research community and pave the way for further research in this direction.

C. Athavipach, S. Pan-ngum, and P. Israsena,Description: For future healthcare applications, which are increasingly moving towards out-of-hospital or home-based caring models, the ability to remotely and continuously monitor patients' conditions effectively are imperative. Among others, emotional state is one of the conditions that could be of interest to doctors or caregivers. This paper discusses a preliminary study to develop a wearable device that is a low cost, single channel, dry contact, in-ear EEG suitable for non-intrusive monitoring. All aspects of the designs, engineering, and experimenting by applying machine learning for emotion classification, are covered. Based on the valence and arousal emotion model, the device is able to classify basic emotion with 71.07% accuracy (valence), 72.89% accuracy (arousal), and 53.72% (all four emotions). The results are comparable to those measured from the more conventional EEG headsets at T7 and T8 scalp positions. These results, together with its earphone-like wearability, suggest its potential usage especially for future healthcare applications, such as home-based or tele-monitoring systems as intended.

J. Liu, X. Shen, S. Song, and D. Zhang,The high inter-subject variability in emotional EEG activities has posed great challenges for practical EEG-based affective computing applications. The recently popular domain adaptation strategy seemed to be a promising technique for addressing this issue, by minimizing the discrepancy of EEG data from different subjects. The present study proposed and implemented an extended Domain Adaptation method by introducing Subject Clustering (DASC). By clustering subjects based on the similarity of their emotion-specific EEG activities, the DASC method could make a flexible use of the available source domain information towards an optimized target domain application. Using the publicly available EEG dataset of DEAP, the DASC method achieved an average accuracy of 73.9±13.5% and 68.8±11.2% for binary classifications of the high or low levels of valence and arousal. Comparison with the state-of-the-art performance as well as the ablation experiments suggests the proposed DASC method as an effective extension to the conventional domain adaptation methods for EEG-based emotion recognition.

PROPOSED SYSTEM

We introduce a robust framework for Emotion Recognition on data collected from Ear Electroencephalogram Device with leveraging the power of supervised learning, with a specific emphasis on Random Forest algorithms. The key performance metric employed in this framework is the handover failure rate. By evaluating mobility concerns, including both premature and delayed handovers, the framework excels in identifying Emotion Recognition in living beings.As an ensemble learning method, Random Forest excels in capturing non-linear relationships and complex dependencies among various health indicators. In the project focused on predicting emotions, Random Forest's ability to build multiple decision trees and merge their predictions can result in a more accurate and robust model. The data from the embedded device was stored and processed on the computer. To begin, preprocessing and feature extraction were carried out in the same manner as on the EEG equipment. Following that, specific models for training on the rich features obtained were proposed. The models were then developed using Tensor Flow. Finally, the models were evaluated and assessed in order to determine the most suitable model for deploying the embedded device.

1. Data Collection Data collection is the systematic process of gathering information from various sources to provide insights, support decision-making, conduct research, and evaluate outcomes. It involves gathering observations or measurements through a systematic approach, encompassing both qualitative and quantitative methods. The collected data is then processed, assessed, and analyzed for research purposes. Methods for data collection may vary across disciplines, including physical and social sciences, humanities, and business.

2. Data Analysis Data analysis is the systematic process of inspecting, cleansing, transforming, and modeling data with the goal of discovering useful information. It involves manipulating data using various techniques and tools to find trends, correlations, outliers, and insights. This process includes cleaning, interpreting, and visualizing data to describe, illustrate, condense, recap, and evaluate information systematically.

3. Feature Extraction Feature extraction is a crucial process in machine learning and data analysis that involves transforming raw data into numerical features while retaining essential information from the original dataset. This reduction in dimensionality aids in simplifying the data and highlighting key characteristics, facilitating more efficient processing and analysis for tasks such as machine learning.

4.Random Forest Application Model Random Forest is a widely used machine learning algorithm that combines the outputs of multiple decision trees to produce a single, robust result. It is commonly employed for both classification and regression tasks, making it versatile across various applications in data science and machine learning.

5. Algorithm Train Algorithm training refers to the process of instructing a computer algorithm to learn patterns, relationships, or rules from a set of training data. It involves exposing the algorithm to examples or instances, allowing it to adjust its internal parameters and optimize its performance based on the provided information. The goal is to enable the algorithm to make accurate predictions, classifications, or decisions when presented with new, unseen data. Training algorithms are a class of smart algorithms that learn from experience and iteratively improve their performance over time. In the context of machine learning, these algorithms are crucial for developing models capable of generalizing patterns and making informed predictions beyond the training data set.

6.Evaluation Evaluation is the structured process of assessing or judging the quality, importance, amount, or value of something. It involves the systematic gathering and analysis of data, both quantitative and qualitative, to determine the impact or effectiveness of proposals, programs, or results. The evaluation process aims to provide insights and inform learning and decision-making by critically examining the objectives, characteristics, and overall worth of the subject under consideration.

7. Test In, model testing is referred to as the process where the performance of a fully trained model is evaluated on a testing set. The testing set consisting of a set of testing samples should be separated from the both training and validation sets, but it should follow the same probability distribution as the training set. 8. Deployment

Deployment in the context of machine learning refers to the process of making a trained model available for use in real-world applications. It involves integrating the model into a production environment where it can receive input data and provide predictions or classifications. Deployment is a crucial step in the machine learning lifecycle, ensuring that the model is operational and can deliver value.

Random Forest Classifier

Random Forest, as an ensemble learning method, can analyze the importance of various features in predicting emotions whether negative, positive and neutral.

Random Forest mitigates over fitting by constructing multiple decision trees and aggregating their results. This is particularly advantageous when dealing with complex datasets, ensuring that the model generalizes well to new instances. For predicting emotions, where individual responses may vary, this robustness is vital for reliable predictions.

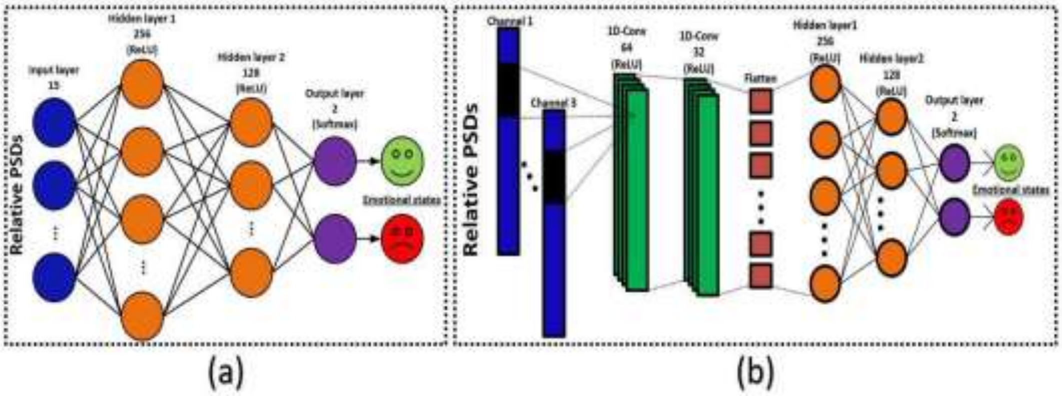

Figure 1. System architecture.

This paper presents the design, implementation, and evaluation of a real-time, on-chip machine-learning system embedded in a behind-the-ear (BTE) wearable electroencephalogram (EEG) device for emotion recognition. The system acquires EEG signals from a compact BTE sensor array, performs low-latency preprocessing and feature extraction on an energy-efficient microcontroller, and classifies emotional states using a Random Forest (RF) classifier optimized for on-chip execution. We evaluate the system on the publicly available DEAP dataset and a custom BTE-collected dataset with five emotional classes (neutral, happy, sad, angry, relaxed). The on-chip RF achieves mean accuracy of 86.2% on DEAP-derived BTE channels and 83.5% on the custom dataset while meeting stringent latency (processing time ≤ 120 ms per window) and energy constraints (average current draw < 8 mA in active processing). We discuss hardware–software co-design choices, feature sets tailored for low-resource devices, quantization and pruning techniques applied to the RF, and real-world considerations including motion artifacts and subject variability. The proposed system demonstrates that robust emotion recognition is feasible on a low-power BTE EEG platform, enabling continuous affective monitoring for healthcare, human–computer interaction, and adaptive systems.

CONCLUSION

In this study, we developed a real-time on-chip embedded system with a 1D-CNN model using behind-the-ear EEG. EEG data acquired from locations behind the ear are of reasonably high quality and are easier to get than data obtained from the scalp. Using FFT, the preprocessed signals are extracted into valuable features from the relative PSDs across five frequency bands. These rich retrieved features were used to implement the three proposed models, namely SVM, MLP, and 1D-CNN, for classifying emotional states. The collected results showed that the 1D-CNN model had the highest performance accuracy in both user dependent and user independent cases. As a result, we selected the 1D-CNN model with recognition. user-independent method to deploy in our embedded system for real-time emotion recognition. TensorFlow Lite was used to deploy the chosen 1D-CNN model to the device. A smartphone application was also developed to make it easier and more comfortable for users. The primary function of this application is to show the output of the EEG-based embedded device with the installed 1DCNN model through the BLE protocol and then to notify users when a negative state is identified. This application can be used to prevent emotional disorders. Several studies have investigated the use of electroencephalography (EEG) signals and machine learning models for emotion classification, including our own research. One such study by Bhosale et al. [33] introduced an adaptation method based on meta-learning for emotion recognition using EEG signals with two classes - Valence and Arousal - on the DEAP dataset. Many other studies have also utilized the DEAP dataset for their research in emotion classification. In addition to employing existing datasets such as DEAP or SEED, some studies have utilized commercial devices or self-made devices to collect and process EEG data for emotional classification. For example, Nguyen and Chung [34] developed a self-made device to collect EEG data from the scalp. Other studies have used EEG signals collected from the ear due to the advantages they offer over scalp EEG. Athavipach et al. [35] developed an in-ear EEG device to classify four emotional classes. However, these studies commonly processed signals and ran machine learning and deep learning models on a PC, without real-time execution.

This limitation restricts the applicability of the studies for real-time and portable applications over an extended period. To address these challenges, our study proposes a lightweight, wearable EEG device that is comfortable for prolonged use, and performs data collection, processing, and deep learning model execution directly on the device in real-time on chip. Table 5 presents a detailed comparison of the relevant information between our proposed system and previous studies. Despite these benefits, our system still has some limitations that need to be considered in future research. Firstly, although this study was conducted on a group of 14 participants (7 males and 7 females) with varying ages, and each participant underwent 20 trials evenly divided between 2 emotional stimuli (negative and positive states) to ensure balance in the dataset, in order to effectively apply our findings to real-world applications, we will conduct experiments on more subjects with more trials, and expand our research to include various other emotional states. Another issue in this study is related to signal processing. Here, we applied a simple band pass filter to eliminate unwanted signals outside the frequency range of 1 to 50 Hz, in addition to instructing the participants to sit comfortably and avoid unnecessary movements that could cause noise interference in the experiment results. The primary purpose of using such a simple filter in signal preprocessing was to reduce the computation time for this process, in order to allocate more time for other important tasks, such as feature extraction or running machine learning models to balance the accuracy achieved and the real-time nature of the system. However, this simple filter has limitations in processing other artifacts caused by the participants during the experiment, such as electromyography (EMG) caused by muscle movements, as it is located in close proximity to the cheek.

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